A Scaled-Correlation based approach for generating and analyzing functional networks from EEG signals

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Abstract. EEG measurements are a valuable resource for analyzing the neuronal functional connectivity associated with different cognitive tasks. By applying different correlation metrics on the processed EEG signal, we aim to define neuronal functional networks (represented as graphs) which are built upon neuronal events and their inter-dependencies. Applying various graph metrics we aim to identify functional patterns that characterize the related cognitive task. Our methods use EEG signals collected in an experiment involving a controlled visual recognition task.

Keywords: EEG, functional brain networks, metrics, Scaled-Correlation, Pearson coefficient, directed peaks weighted network

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1 Introduction

The task of finding out how the areas of the human brain communicate as a function of cognitive tasks is still an open research participant. Cognitive processes are known to engage large populations of neurons in the brain and it becomes critical to understand how these populations are coordinated across large spatial scales.

In order to tackle this problem we focus on the functional connectivity of the brain during a conscious visual perception task. Our main objective is to identify functional networks of the brain and analyze their static and dynamic properties. We apply correlation functions not previously used to the best of our knowledge on EEG signals, in order to generate new types of functional networks. The EEG signals were recorded during a controlled task of visual perception [5]. The traditional procedure to extract functional networks is to use the pairwise Pearson correlation coefficient to determine if pairs of nodes in the network are functionally connected. Here, we explore a novel approach, whereby functional interaction is estimated using Scaled Correlation function [11] and the resulting links represent the delays between corresponding pairs of EEG signals. The challenge is to determine which type of extracted network correlates better to the cognitive tasks that participants have to solve.

We focused on two different types of networks: Pearson Coefficient Weighted Networks (PCWN) and Peaks Scaled Correlation Weighted Networks (PSCWN), and for each we evaluated network theory metrics.

2 Related Work

There are three types of neuronal connectivity considered in literature [1]: structural, functional, and effective. Structural connectivity deals with discovering the physical structure of the brain. It is measured using techniques such as functional Magnetic Resonance Imaging (fMRI) and Diffusion Tensor Imaging (DTI). Functional connectivity relies on the set of inter-dependencies between neural events. As opposed to the underlying structural connectivity, it is dynamic and dependent on the cognitive activity [2]. Functional connectivity is usually estimated by pairwise associations between recordings of neuro-imaging. Effective connectivity shows the influences brain areas have on each other. We concentrate on the functional connectivity because it reflects the interactions between different brain areas related to various cognitive tasks.

The basic theoretical framework for graph/network analysis of functional connectivity is given in [3], with more advanced metrics being defined in [4]. The cited authors define the steps necessary to analyze EEG/MRI data using graph theory in order to study brain network organization during both resting-state and cognitive tasks.

It is believed [6] that the gamma EEG band (30-80 Hz) is relevant to conscious visual perception. To study the interactions in this band we used the Scaled Correlation algorithm [11], which can be used to compute correlations expressed on fast timescales.

The community and hub structure dynamic was studied in [12], that concludes that increasing cognitive task difficulty leads to lower modularity, fewer provincial hubs, and more connector hubs.

The relevance of network size was studied in [13], showing that different metrics depend on it (i.e. clustering coefficient, modularity, efficiency, economic efficiency and assortativity). The conclusion was that efficiency, assortativity were higher and modularity was lower on large networks compared to smaller networks, even though their density was the same.

Also, a related approach was presented in [14] by computing partial correlations between the pairs of two signals. Partial correlation consists of calculating PCC but augmenting this coefficient in order to eliminate the influence of potential third-party signals. One of the most important conclusions that were made is that using first grade partial correlations the distribution of values are centered around zero whereas non-partial correlations (simple PCC) were spread along the [0,1] interval.

Our work uses the EEG activity data recorded using the task described in [5]. The participants had to recognize images on a screen, without time restrictions. The images were transformed in order to be harder to recognize. Our objective was to use these signals to study the structure and some properties of functional brain networks related to the visual recognition activity.

3 Relevant Concepts

A **participant** is defined as one of the individuals that took part in the experiment, and for which there is specific data.

A **trial** is a part of an experiment, time-wise. An experiment is divided into several trials (in our case, 210 trials), and each trial contains some events. In this experiment the trials have different lengths, as the participants were free to explore. An **event** consists of a specific time instant relative to the beginning of the trial and a unique code which has significance for the experiment.

EEG data was recorded using a Biosemi ActiveTwo machine with 128 unipolar channels, yielding 128 EEG signals.

A **correlogram** is the result of scaled-correlation function [11] applied on two signals. As the correlogram is an array of values, the **peak** of a correlogram is the maximum absolute value along all values. The **lag** is the position where the **peak** was found in the correlogram.

The **stimulus** refers to the moment when the picture is displayed on screen. We call **baseline** the moment right before the stimulus appears.

4 Identification of functional networks

For each participant and for each trial, we do the following steps: first, using the recorded signals, we construct a graph that estimates the functional connectivity, and then we apply metrics from complex network theory on these graphs (Figure 1). These steps are further explained in the following paragraphs.

The first phase consists of parsing the EEG signals recorded from the participants. Based on these signals we compute various correlation functions. We use two types of functions: Scaled-Correlation (SC) [11] and Pearson Correlation Coefficient (PCC). Based on the resulted scaled-correlogram (in case of SC) we identify lags and peaks. In case of PCC we simply use it without further processing. The decision of using PCC is based on its frequent use in literature.

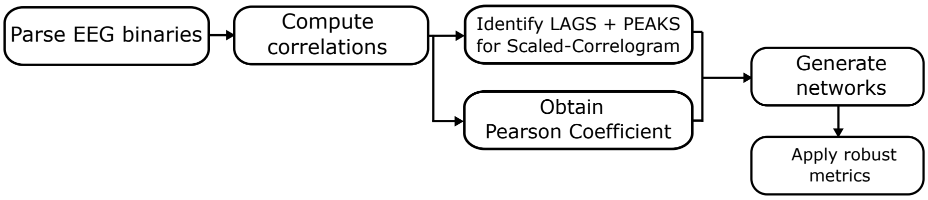

Fig. 1. Lags, Peaks and Pearson weighted networks approach used

However this coefficient fails to represent the timing relation between signals, its value representing only the instantaneous correlation at lag zero. In contrast, SC slides the signals in time in order to find the highest correlation moment which could identify delays that indicate potential causality between signals.

In the next phase, we create three kinds of graphs, referred by us as the PSCWN (Peaks Scaled Correlation weighted Network), LSCWN (Lags Scaled Correlation weighted Network) and the PCWN (Pearson Coefficient weighted Network). All these graphs have 128 nodes, corresponding to the EEG channels.

The *PCWN* is an undirected weighted graph which has the absolute values of the Pearson correlation coefficient (samples version) as weights between any two nodes. The Pearson correlation coefficient shows how linearly correlated two signals are: if it is 1, the signals are perfectly linearly correlated, and if it is -1, they are perfectly anti-correlated. A correlation value 0 indicates no correlation at all between given signals.

The *PSCWN* is a directed graph which has on edges the absolute values of the peaks from the scaled-correlogram [11] whereas the *LSCWN* is a directed graph as well but contains on edges the absolute values of the lags. The absolute peak value is the strongest correlation value at time t. As we mentioned a negative correlation indicates the anti-correlation which is perfectly fine because it means that most probably the two signals come from opposite electrodes sites. The lag indicates the delay of information transfer hence the bigger the distance from 0, the higher delay it is obtained no matter if it is negative or positive. In the case of the PSCWN the direction of the edge is defined by the lag. Considering the correlation of channel A and B, a positive lag shows B leading A while a negative lag shows A leading B. When the lag is 0, we consider that the channels are instantaneously correlated and we assign two bidirectional edges (from A to B and from B to A). For channels with the same index (diagonal) the value in the matrix is zero.

For the window of the cross-correlogram we have chosen a window of +/-100 ms, which has the effect of focusing on small delays. For the Scaled Correlation we applied a scale window segment of 25 ms to keep only correlations between components that have a frequency greater than 40 Hz. We have chosen to use both Pearson-based and Scaled-Correlation-based networks to compare results obtained with the traditional method with those where only the fast correlations of the signals are retained which is considered to be important for conscious visual perception [6].

For each network we decided to reduce their densities (about 50% of the lowest weights). The motivation behind this action is the extremely high density of PCWN which is a complete graph, hence all metrics would lead to improper results (e.g. global clustering coefficient will be 1, average path length will be 1 as well, etc.). We chose to take the absolute value because negative edge weights are not supported by many graph algorithms, but negative correlations are also relevant in the function of the brain.

The following measures have been applied and analyzed: average path length (APL) [9][7], global clustering coefficient (GCC) [8], betweenness centrality (BC) and closeness centrality (CC) [9]. For each measure we study the modifications of global network statistics by comparing SC and PCC.

5 Experimental results

5.1 Data description

The data we used consists of the results of [5]. We analyzed 10 participants, each with 210 trials, each trial being structured into events with specific codes. The important event codes in the context of this paper are: 150, which represents the white screen appearing in front of the participants, 129, which is the moment the stimulus is first presented, and 1,2,3 which are the response types: 1 = seen, 2 = uncertain, 3 = nothing. The time between event 150 and event 129 is referred to by us as *baseline*, and the time between 129 and 1,2 or 3 is referred by us as *stimulus*. The trials are split in 7 groups, where each group has a higher value of g (parameter that controls how recognizable the image is) than the previous one. There are 128 EEG channels corresponding to 128 electrodes. The sampling rate is 1kHz.

The process of computing the correlations starts with the raw data represented as a matrix of floating-point values. Each row is considered to be a channel (a total of 128 rows). Each participant alone will have a different number of trials for each stimulus, depending on the given responses. For example, for the first participant we have 63 trials where he recognized the stimulus, 53 trials where he was uncertain and 94 trials where he recognized nothing; for the second participant the numbers are different. Once all trials are parsed and gathered from the raw data, SC and PCC can be applied. The networks obtained are represented as adjacency matrices. Each matrix is a squared one (128 rows and columns). On primary diagonal all values are zero (even though we know that a signal correlated with itself - named auto-correlated, will result in a fully correlated signal), in order to eliminate the potential influence on results. PSCWN contains for each pair of [row, column] a value (between [0, 1]) representing the peak of the correlation result. In the case of LSCWN, the value is the lag where the peak is positioned in the scaled-correlogram. Finally, for PCWN the values are between [0, 1] at lag = 0 (signals were not slid in time at all).

For PSCWN, LSCWN and PCWN the density is reduced by eliminating 50% of the weakest edges. In case of LSCWN, the density reduction is done by considering the actual correlations (PSCWN) instead of the lags. We deal with two different types of metrics: distance based (APL, BC, CC) and connection based (GCC). Because we end up with a binary network for the PCWN (if the value is different from zero, then it is a one), binary network is considered as well for the PSCWN in order to allow results comparison. In the next section we describe the comparisons between Scaled Correlation based networks and Pearson Correlation based networks.

5.2 Results

After generating candidate functional brain networks, we applied the metrics mentioned in the previous chapter in order to identify the neuronal activity in time and related to different cognitive outcomes.

Average Path Length
In Fig. 2 we display the APL for the baseline and the stimulus of the three cases (i.e., seen, uncertain, unseen) for each individual participant. The APL value in the baseline case is roughly the same over the participants having a small variance in case of PCWN. However for LSCWN the variation seems to be in the same interval across participants even though this is higher. This is showing that the idle state is behaving similarly across participants. Also for the stimulus it is notable that when the communication correlates with visual perception, the communication between nodes is more efficient compared to other cases. As a comparison between PCWN and PSCWN, it can be seen that using Scaled Correlation, the results indicate an obvious behavior meaning that the time component and spotted fast components (faster than 40Hz) are significantly trimming down the common behavior.

Global Clustering coefficient
The next result obtained is shown in Fig. 3 where the GCC metric is analyzed as the mean of all the trials corresponding to the related stimulus type. First of all it is important to notice that no matter of the stimulus type the GCC is lower in the baseline. We would expect for the Seen case, this value to be slightly higher than the rest of the cases because the brain should be more connected when recognizing the observed object. It seems to be an average of ≈ 0.7 along all conditions which highlights an uniform behavior of the brain regarding how functionally connected its areas are (areas denoted by electrodes). Also it is noticeable that the variation intervals for PSCWN are hardly overlapping whereas for PCWN for both stimulus and baseline, all the variations seem to be in the same interval hence not indicating something relevant.

Betweenness Centrality and Closeness Centrality
The BC and CC are illustrated in Fig. 4 and 5. For both metrics it can be seen that in the baseline the variation of the values fluctuates in a large interval

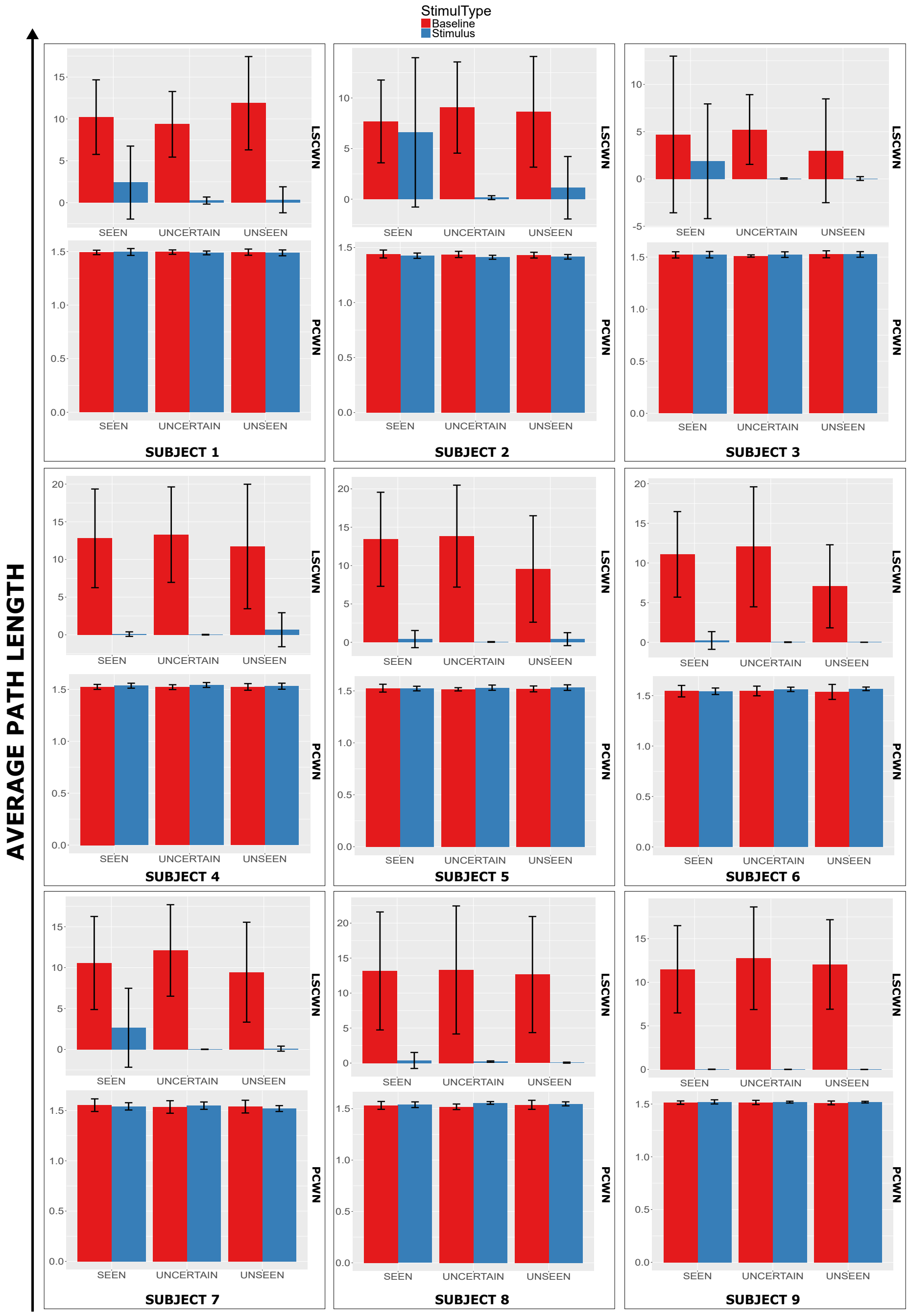

Fig. 2. Average Path Length (APL) applied on LSCWN and PCWN. For LSCWN we used segment size $s = 25ms$ (fast events - 40Hz). For both networks the density was reduced with 50%. The value obtained is the mean value across all trials. Also standard deviation was computed.

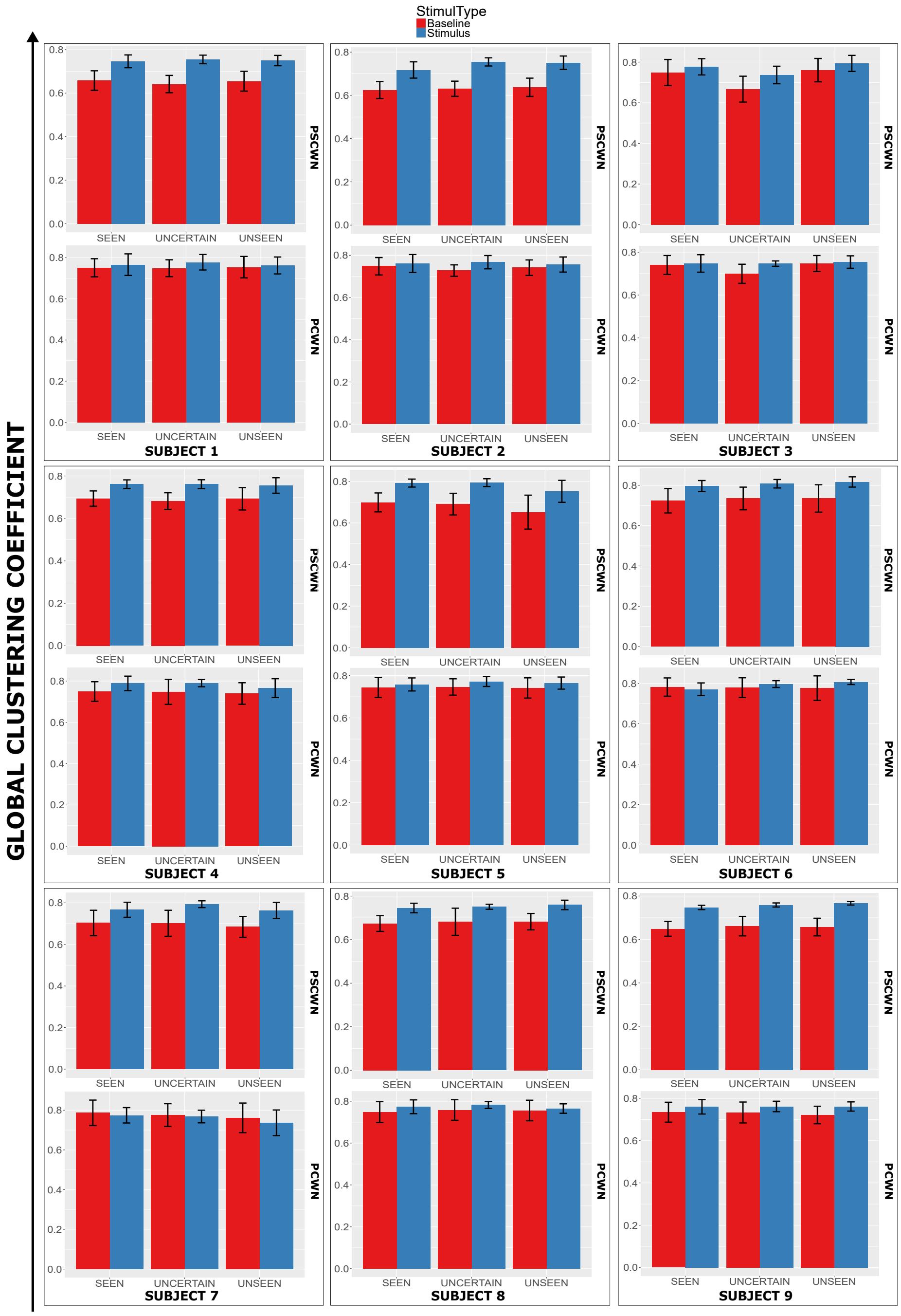

Fig. 3. Global Clustering Coefficient (GCC) applied on PSCWN and PCWN. For PSCWN we used segment size $s = 25ms$ (fast events - 40Hz). For both networks the density was reduced with 50%. The value obtained is the mean value across all trials. Also standard deviation was computed.

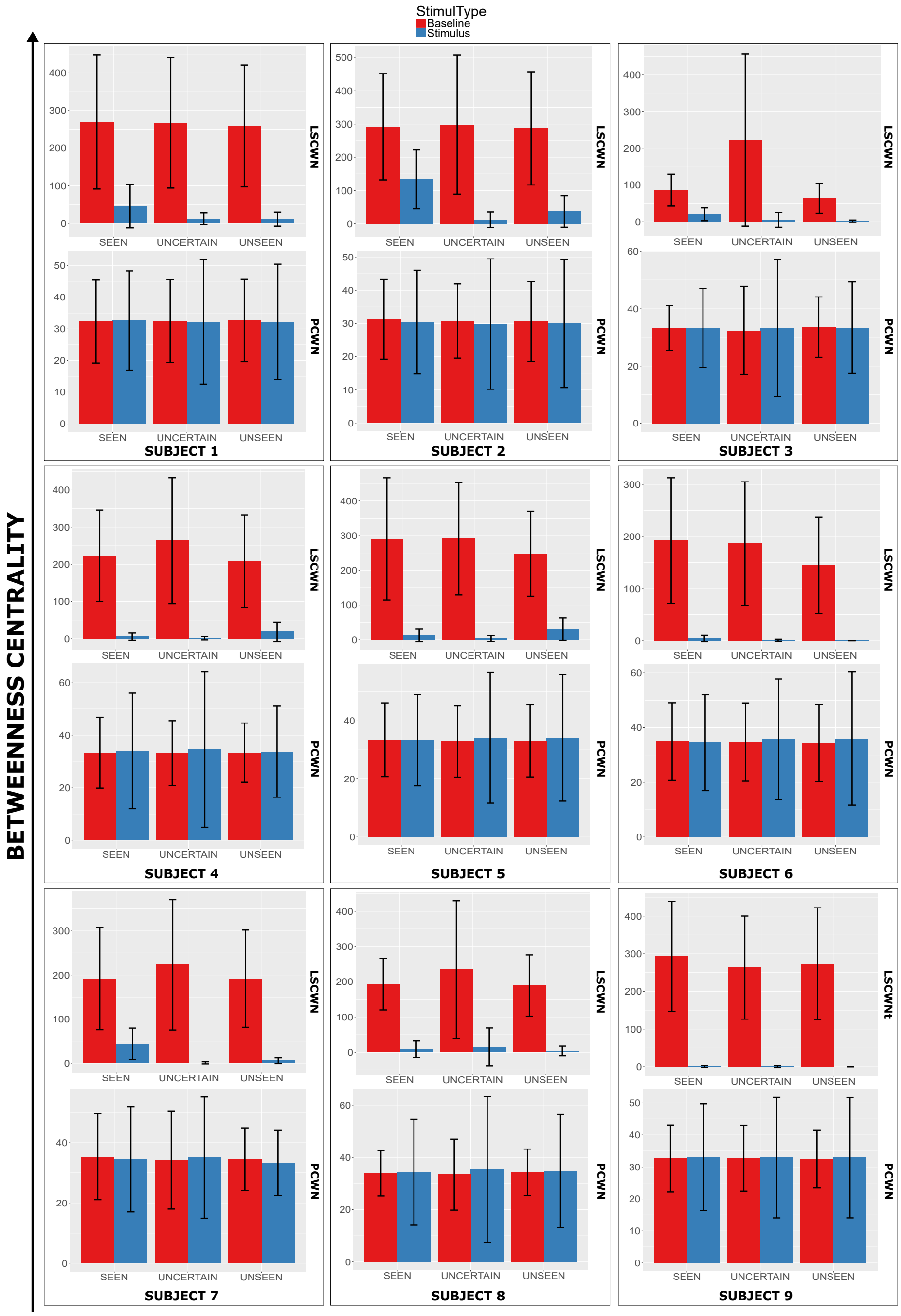

Fig. 4. Betweenness Centrality (BC) applied on LSCWN and PCWN. For LSCWN we used segment size $s = 25ms$ (fast events - 40Hz). For both networks the density was reduced with 50%. The value obtained is the mean value across all trials. Also standard deviation was computed.

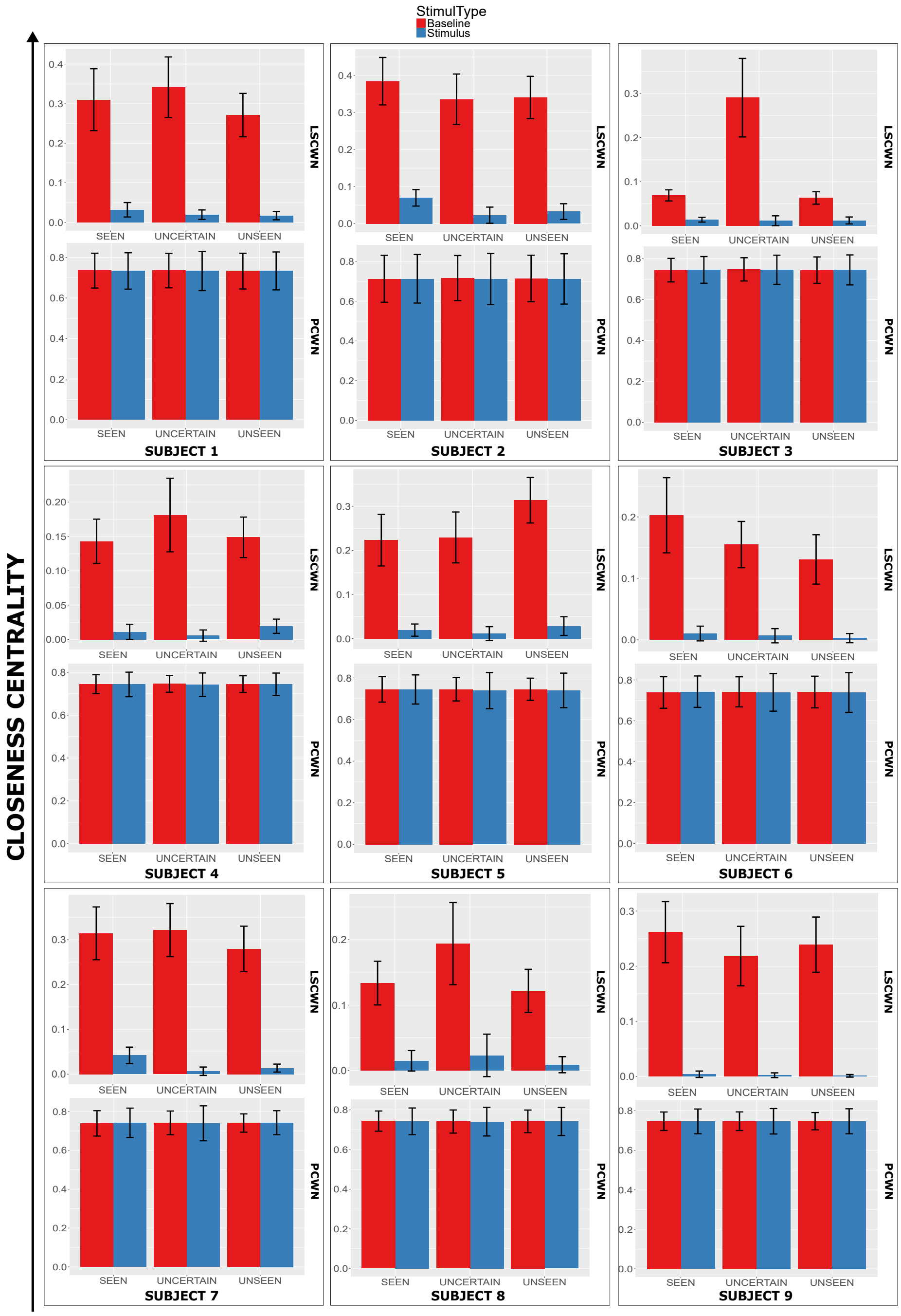

Fig. 5. Closeness Centrality (CC) applied on LSCWN and PCWN. For LSCWN we used segment size $s = 25ms$ (fast events - 40Hz). For both networks the density was reduced with 50%. The value obtained is the mean value across all trials. Also standard deviation was computed.

($\approx [100 - 400]$) meaning that some parts of the neuronal areas are highly active whereas others are not involved that much in communication. Results show that the appearance / presence of the stimulus on the screen is associated with equal involvement from all region corresponding to the electrode sites. This highlights the fact that most of the nodes are contributing to efficiently diffuse the information (having similar closeness) by presenting a relative low variation. Again the PCWN does not offer any informative results by showing extremely similar variations across participants and across baseline and stimulus.

6 Conclusion

The human functional brain network is one of the most complex ones, especially when taking into account its dynamics. Analyzing these networks helps us identify different behaviors and characteristics of the brain by using various types of cross-correlation functions. As wen have seen, the Pearson Correlation Coefficient and the Scaled Correlation method offer different results. For almost all cases the PCWN shows no relevant results and this can happen because it does not consider the temporal structure of the correlations. However fast component filtering (40Hz for Scaled Correlation) seems to offer interesting results that correlate to the visual task. In conclusion our proposed approach is meant to offer another analysis perspective: the causality between neuronal areas and how much of the similar information is exchanged. This method of constructing new functional networks can be extremely useful to study the cognitive behavior of the brain under different various cognitive tasks. Further work can be done by considering the cross-correlation function and identification of the brain areas (occipital, frontal, parietal, temporal) and to analyze how these cooperate to fulfill a specific cognitive task. If analyzing specific nodes is a target then it is worth to continue with the *Betweenness Centrality* and the *Closeness Centrality* metrics. If the target is the network itself then the *Average Path Length* and *Global Clustering Coefficient* may represent excellent metrics to go with.

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